EVALUATING GEOSPATIAL VARIANTS OF USLE TOPOGRAPHIC AND COVER FACTORS USING DIGITAL CLOSE RANGE PHOTOGRAMMETRY AND LEGACY TOPOGRAPHIC SURVEY DATA

A THESIS PRESENTED TO THE DEPARTMENT OF HUMANITIES AND SOCIAL SCIENCES IN CANDIDACY FOR THE DEGREE OF MASTER OF SCIENCE

By JACOB DÉGAYNER

NORTHWEST MISSOURI STATE UNIVERSITY MARYVILLE, MISSOURI NOVEMBER, 2013
EVALUATING GEOSPATIAL USLE VARIANTS

Evaluating Geospatial Variants of USLE Topographic and Cover Factors

using Digital Close-Range Photogrammetry and Legacy Survey Data

Jacob DeGayner

Northwest Missouri State University

THESIS APPROVED

Thesis Advisor, Dr. Yanfen Le

Date

Dr. Patricia Drews

Date

Dr. John Pope

Date

Dean of Graduate School

Date
Evaluating Geospatial Variants of USLE Topographic and Cover Factors

Abstract

Accelerated soil loss is a major problem threatening natural and cultural resources in the arid Southwest. Accurate assessment of the scale of erosive processes is essential for making sound resource management decisions. While the Universal Soil Loss Equation can be used with flexibility in a GIS environment to estimate soil loss, the number of factor calculation methodologies leave uncertainty as to the most appropriate method. This study used varying methodologies for calculating the USLE S (slope inclination) and C (land cover) factors using remotely sensed data and evaluated their suitability using a comparison between a 1965 aerial photogrammetric survey and 2013 site conditions using digital close-range photogrammetry. Photogrammetric models were georeferenced to the project coordinate system using reflective targets measured using an electronic theodolite. The 2013 survey sampled approximately 14,000 square feet at five sites within the study area, finding a mean vertical decrease of approximately 0.24 feet and net soil loss of approximately 3,333 cubic feet over the course of the 48-year period of study. With the exception of one sample site, model predictions underestimated soil losses as measured.

The study compared three C (land cover) factor calculation techniques published by De Jong (1994), Van der Knijff et al. (1999), and Suriyaprasit and Shrestha (2008), as well as three methods for calculating the effect of slope inclination, published by McCool et al. (1987), Nearing (1997), and Mitasova and Mitas (1999). The study found that the
values calculated by Van der Knijff et al. (1999) equation generally contributed to estimates with higher levels of agreement with field. A possible explanation for this is the history of soil disturbance at the study site. C factor calculation technique was identified as the most important decision for future soil loss estimates at the site. While the S factor equation of McCool et al. 1987 was included in the variant with the highest levels of agreement at the sample site and slope unit scales, the differences between all three S factor methodologies were small and generally contributed to similar estimates. The study was able to identify a combination of remotely sensed parameter calculation equations which yielded soil loss estimates superior to those of other equations tested.
Table of Contents

Abstract ........................................................................................................................................ iii

Table of Contents ...................................................................................................................... v

List of Figures ............................................................................................................................ vii

List of Tables .............................................................................................................................. x

List of Equations ......................................................................................................................... xii

Chapter 1: Introduction .............................................................................................................. 1
  Description of Study Area ........................................................................................................ 3
  Research Question .................................................................................................................. 6
  Justification ............................................................................................................................. 6

Chapter 2: Literature Review ................................................................................................... 8
  Quantifying Erosion Risk ....................................................................................................... 8
  USLE Model Summary .......................................................................................................... 10
  Model Variation ...................................................................................................................... 12
  The USLE and GIS ................................................................................................................ 13
  Surface Modeling with Close-Range Digital Photogrammetry ............................................. 16

Chapter 3: Conceptual Framework and Methodology ........................................................... 18
  Description of Data Sources ................................................................................................. 18
  Description of Methodology ................................................................................................. 21
    Phase 1: Data Preparation .................................................................................................. 22
    Phase 2: Soil Loss Modeling .............................................................................................. 28
    Phase 3: 2013 Topographic Sampling ............................................................................. 39
    Phase 4: Model Evaluation ............................................................................................... 50

Chapter 4: Analysis Results and Discussion ......................................................................... 52
  Cell Level Analysis ............................................................................................................... 52
  Site Level Analysis ............................................................................................................... 55
  Slope Unit Analysis .............................................................................................................. 59
  Topographic factor discussion ......................................................................................... 62
List of Figures

Figure 1: The ruins of the second Fort Bowie from atop Overlook Ridge....................... 4
Figure 2: Study area overview ..................................................................................... 5
Figure 3: Example of 1966 topographic survey sheet .................................................. 19
Figure 4: Methodology flowchart .................................................................................. 22
Figure 5: Georeferencing schema of sheet thirteen ...................................................... 23
Figure 6: Digitized 1965 survey data ............................................................................. 26
Figure 7: 2.5 dimension perspective view of survey sheet fourteen.............................. 27
Figure 8: R Factor raster in vicinity of study area ......................................................... 29
Figure 9: Interpolated R factor ....................................................................................... 30
Figure 10: USLE L Factor with inset showing flow concentration ................................. 31
Figure 11: S factor calculation variants ........................................................................... 32
Figure 12: NRCS soil survey map units and K factors .................................................. 34
Figure 13: NAIP, Quickbird, and final NDVI images ..................................................... 36
Figure 14: USLE C factor variants .................................................................................. 37
Figure 15: Damaged control monument (left) and buried control monument (right)...... 41
Figure 16: Sampling locations and total station resections .......................................... 43
Figure 17: Site setup at sample site #1 showing total station (foreground) and targets
(background) ................................................................................................................ 44
Figure 18: Target marked on photo with sub-pixel accuracy ........................................ 47
Figure 19: Processing a stereo pair from Site 3 in Photomodeler Scanner ................... 49
Figure 20: Mean soil loss measurements and model variant predictions .................... 58
Figure 21: Slope Units ............................................................. 60
Figure 22: Predictions, measured losses, and exponential trends for three variants with highest levels of agreement ................................................................. 62
Figure 23: S factor and slope chart for sites sampled .................................................. 65
Figure 25: Estimated annual soil loss using McCool et al. (1987) and De Jong .......... 75
Figure 26: Estimated annual soil loss using McCool et al. (1987) and Suriyaprasit and Shrestha (2008) ................................................................. 76
Figure 27: Estimated annual soil loss using McCool et al. (1987) Van der Knijff et al. (1999) ................................................................. 77
Figure 28: Estimated annual soil loss using Mitasova and Mitas (1999) and De Jong (1994) ................................................................. 78
Figure 29: Estimated annual soil loss using Mitasova and Mitas (1999) and Suriyaprasit and Shrestha (2008) ................................................................. 79
Figure 30: Estimated annual soil loss using Mitasova and Mitas (1999) and Van der Knijff et al. (1999) ................................................................. 80
Figure 31: Estimated annual soil loss using Nearing (1997) and De Jong (1994) .. 81
Figure 32: Estimated annual soil loss using Nearing (1997) Suriyaprasit and Shrestha (2008) ................................................................. 82
Figure 33: Estimated annual soil loss using Nearing (1997) and Van der Knijff et al. (1999) ................................................................. 83
Figure 34: Sample site 1 project overview ................................................................. 84
Figure 35: Sample site 2 project overview ................................................................. 85
Figure 36: Sample site 3 project overview ................................................................. 87
Figure 37: Sample site 4 project overview ................................................................. 88

Figure 38: Sample site 5 project overview ................................................................. 89
List of Tables

Table 1: Georeferencing RMSE table ................................................................. 24
Table 2: S factor statistics ............................................................................... 33
Table 3: C factor statistics ............................................................................... 38
Table 4: Standard error values for total station setups (ft) .............................. 42
Table 5: Cell level soil loss regression statistics ............................................. 52
Table 6: Cell level absolute value topographic change regression statistics .... 53
Table 7: Regression statistics on cell experiencing net erosion ...................... 54
Table 8: Net soil loss and predictions by sample site ....................................... 56
Table 9: Variant agreement on areas experiencing net erosion ...................... 57
Table 10: Variant agreement at the slope unit level ......................................... 61
Table 11: Topographic component regression statistics .................................... 63
Table 12: Topographic factor component variance .......................................... 64
Table 13: Zonal C factor statistics aggregated by vegetation formations defined by Sonoran Desert Network 2008 ................................................................. 66
Table 14: C Factor table for permanent pasture, range, and idle land (Wischmeier and Smith 1978, p. 32) ................................................................. 67
Table 15: Regression statistics comparing C factor variants and soil loss ......... 69
Table 16: Sample site 1 photogrammetry project quality ................................. 84
Table 17: Sample Site 2a photogrammetry project quality ............................... 85
Table 18: Sample Site 2b photogrammetry project quality ............................... 86
Table 19: Sample Site 3a photogrammetry project quality ............................... 87
Table 20: Sample Site 3b photogrammetry project quality ............................... 87
Table 21: Sample Site 4 photogrammetry project quality .................................................. 88
Table 22: Sample Site 5 photogrammetry project quality .................................................. 89
List of Equations

Equation 1: Soil loss equation from Zingg (1940) ................................................................. 9
Equation 2: Soil loss equation from Smith and Whitt (1948) .................................................. 9
Equation 3: The Universal Soil Loss Equation (Wischmeier and Smith, 1978) ......................... 10
Equation 7: Slope length calculation modified for upslope contributing area (Mitasova and Mitas, 1999) .............................................................................................................. 15
Equation 8: De Jong (1994) C factor calculation ...................................................................... 15
Equation 9: Van der Knijff et al. (1999) C factor calculation .................................................... 16
Equation 10: Suriyaprasit and Shrestha (2008) C factor calculation ........................................ 16
Chapter 1: Introduction

Soil loss from water erosion is an important process affecting resource management at National Park Service (NPS) units, especially in arid climate zones dominated by monsoonal climate patterns. While some degree of loss is inevitable, accelerated erosion adversely impacts the ecological health of natural resources, risks damage to park facilities and historic structures, destroys the invaluable archeological context of cultural resources, and even threatens the safety of visitors and employees. An understanding of how erosive processes are operating under varying conditions can give resource managers valuable decision-making tools to advise restoration efforts, cultural resource preservation treatments and data recovery operations, and preventative measures.

Several soil loss models have been developed to estimate and predict soil losses due to water erosion. The first to achieve widespread use was the Universal Soil Loss Equation (USLE) by Wischmeier and Smith (1978). The USLE is based on a massive volume of empirical observations at study plots under a variety of conditions and calculates annual soil loss estimates as the product of five factors: climate, soil, slope length and slope steepness, land cover, and land support practices. As recognition for the efficacy of the USLE model increased, improvements were made in order to apply the concepts of USLE to general soil conservation. This resulted in the publication by Renard et al. (1997) of the Revised Universal Soil Loss Equation (RUSLE), which was introduced in an effort to model erosion at finer scales and broader sets of circumstances.
The purpose of this study is to evaluate geospatial variants of USLE factor calculation methods which can be readily deployed at other study areas. The entirety of input data for some USLE variants can be obtained from widely available, remotely sensed datasets such as satellite imagery and the National Elevation Dataset (NED). The intricacies of the RUSLE subfactors allow for an extremely in-depth accounting of erosive processes, but the large amount of field data collection makes RUSLE more difficult to implement on a landscape approach. Tiwari et al. (2000) found that model efficiencies between USLE and RUSLE are quite comparable, with the USLE achieving higher efficiency for the particular study. As a result, many studies, including this thesis, use combinations of factor calculation methodology from both the USLE and RUSLE to derive soil estimates, based on study area scale and data availability.

Since the USLE and RUSLE involve the combination of factors which all vary spatially and relatively independently of each other, GIS is an ideal tool for applying the USLE and RUSLE to estimate erosion at landscape scales. Several alternate methodologies have evolved for estimating USLE factors from remotely sensed spatial data. The integration of the USLE with GIS can be an effective tool to analyze and visualize the distribution and severity of erosive forces throughout a study area. This allows the analysis of soil loss at landscape scales with a drastically reduced amount of field work. Warren et al. (1989) were among the first to demonstrate the utility of this approach. Although techniques for calculating USLE parameters have subsequently been modified and refined, the relatively simple multiplicative nature of the USLE model lends itself well to raster GIS processing, which continues to drive the model’s popularity worldwide (Xu et al. 2008).
The flexibility of calculating the USLE input factors implies both advantages and ambiguities. Multiple approaches allow for increased freedom in terms of input data and analysis scale, but leave doubt as to the most effective method. The historical topographic information captured may present the opportunity to compare soil loss predictions with actual quantities of soil loss, indicating the most appropriate soil loss estimation method.

This project attempted to evaluate the predictive utility of several calculation techniques used to derive the slope steepness and land cover factors of the USLE at Fort Bowie National Historic Site, an abandoned military outpost and surroundings managed by the National Park Service in southeastern Arizona. This was accomplished by integrating elevation data derived from a 1965 topographic survey with other soil model input data to generate soil loss predictions and comparing these predictions to current topographic conditions as measured using digital close-range photogrammetry. Digital close-range photogrammetry is the science of extracting 3D information from digital photographs taken from the ground or low-altitude platforms.

Description of Study Area

Fort Bowie National Historic Site is located in the northern reaches of the Chiricahua Mountains in southeastern Arizona. Fort Bowie’s geographic characteristics have long made it a place of cultural importance. The Fort is situated in Apache Pass, an important travel corridor from the pre-Columbian Ceramic period to the latter 19th century, when the Butterfield Overland Mail Route passed through on the way to San Francisco. The site also contains Apache Spring, a rare source of perennial water in the
arid Sonoran highlands which made control of the pass of great strategic value. These geographic features provided context for the Apache Wars, a 30-year conflict between the United States Army and the Chiricahua Apaches. The first Fort Bowie was constructed in 1862 to support U.S. military operations, and a larger fortification was built in 1868. Figure 1 is a picture of the ruins of the second Fort Bowie.

![Figure 1: The ruins of the second Fort Bowie from atop Overlook Ridge](image)

The physical geography of Fort Bowie National Historic Site exemplifies the “sky island” basin and range geography common in the arid Southwest. Vegetation is characterized by semi-desert grassland at the lower elevations and lower Madrean woodland at higher altitudes. Fort Bowie’s climate is dominated by a monsoonal
precipitation pattern, with the mid to late summer experiencing a large portion of annual rainfall.

Figure 2 presents the study area as well as the individual slopes and small catchments selected for sampling. See Chapter 3 for sample site selection rationale. If this pilot study proves useful for park resource management, a project will be initiated to convert the remaining survey sheets at Fort Bowie and other park units possessing similar data to increase the spatial extent of soil loss estimation.

Figure 2: Study area overview
Research Question

Based on measurements of topographical change between 1965 and 2013, which combination of USLE topographic and land cover calculation techniques is most suitable for predicting future erosion patterns at Fort Bowie National Historic Site?

Justification

Soil transport due to water erosion has been identified as one of the most important processes affecting the natural and cultural resources of Fort Bowie National Historic Site. In a recent study, Hubbard et al. (2010) conducted condition assessments on fifteen backcountry archeological sites at Fort Bowie NHS, finding that thirteen sites (87%) were visibly impacted by erosive processes. Accelerated erosion has been found to have detrimental effects to natural resources as well. Nauman (2010) developed an erosion assessment and mitigation plan for the Apache Spring watershed at Fort Bowie NHS, citing concerns from park resource management that soil losses are impacting aquifer infiltration and inhibiting the reestablishment of native vegetation communities. Nauman (2010) mapped 551 active erosional features within the study area, noting that historic disturbances associated with the military presence likely contributed to the severity of soil loss.

An understanding of the extent and severity of erosive forces is essential for implementing conservation practices. For example, knowledge of areas most likely to experience heavy erosion in coming years is a valuable tool with which to prioritize condition assessments on archeological sites which may be both inherently vulnerable and located in one of the more erosion-prone locations in the park. An accurate
accounting of erosion rates affords the ability to justify and prioritize preservation expenditures in a climate of reduced fiscal resources. This project endeavors to identify the most appropriate model to be used in similar assessments, as well as evaluating a methodology with which to implement future studies. Additionally, the analysis of forty-eight years of topographic change presents the opportunity to calibrate model parameters to the conditions of the study area, resulting in a model of increased accuracy at local scales.

In addition to the aforementioned goals, the project also provides beneficial side products to be of future use to resource management at the park. Not least of these is a digitized elevation dataset in both raster and vector format, which represents the highest quality elevation layer in the Fort Bowie’s GIS library to date. This project also produced methodological documentation on the process and feasibility of modeling topography using close-range digital photogrammetry. This method of field data collection is experiencing an increase in use in national parks for a variety of projects which benefit from its diverse applications, such as architectural documentation, archeological site mapping, and monitoring hydrological channel morphology.
Chapter 2: Literature Review

Quantifying Erosion Risk

In a study at Tonto National Monument in central Arizona, Nauman and McIntyre (2008) used Water Erosion Prediction Project (WEPP), a process-based soil loss and runoff simulation model, to assess localized erosion impacts at forty-six sites within the monument. The study found that average erosion on the sites studied ranged from .004 to .333 kg/m$^2$ annually. Vegetation removal, a common site stabilization practice to mitigate the effects of root growth and eventual decay on subterranean artifacts and architecture, was a central focus of that study. Nauman and McIntyre (2008) concluded that sites located at the bottom of long, steep slopes relatively devoid of vegetation were exposed to greatest risk for damage from high-volume rain events, and preservation efforts are likely necessary to prevent archeological information loss prior to the next major monsoon events. While the study did not draw a direct correlation between vegetation removal practices and erosion potential, the authors advised that “vegetation removal must be considered strongly as a possible cause of the increase of susceptibility of sites to erosion” (Nauman and McIntyre 2008, p. 12).

The empirical description of soil loss was initiated by a United States Department of Agriculture (USDA) policy of land protection and accelerated by widespread erosion-related phenomena such as the “Dust Bowl” of the 1930’s, when approximately 20% of arable lands in the United States were subject to serious erosional impacts (Rodriguez and Suarez 2010). Baver (1933) developed the first empirical equation to estimate soil losses based on study plot observations and basic soil properties such as particle size and permeability.
Zingg (1940) developed the first comprehensive equation predicting soil erosion based on combined rainfall, soil management, and topographic factors:

\[ A = \lambda^{0.6} s^{1.4} \]  

(Eq. 1)

A represents mean soil loss per unit area, \( \lambda \) is slope length, and \( s \) percent slope based on a tangent calculation. Although Zingg’s (1940) equation was replaced with alternatives due to consistent underestimation (Rodriguez and Suarez 2010), its ability to account for all of the major factors contributing to soil erosion in mathematical form was influential to the field. Musgrave (1947) and Smith and Whitt (1948) used the growing amount of study plot data to derive the following:

\[ A = 0.025 + 0.052 s^{4/3} \]  

(Eq. 2)

The two equations mentioned above were milestones in soil erosion modeling, but were constrained by the regional characteristics of their study plots. Wischmeier and Smith (1957, 1965, and 1978) sought to develop a model that could be applied broadly to agricultural soil loss. To do this, they fit a series of equations to aggregated study plot data from throughout the contiguous United States using a combination of simulated rainfall and natural observations. Wischmeier and Smith’s model became known as the Universal Soil Loss Equation, published in 1965 for agricultural applications in the eastern United States and revised for expanded use in 1978.
USLE Model Summary

The USLE model is calculated as the simple product of the five input factors described below. A key concept in the USLE is the unit standard plot. The values of the input factors were derived from empirical measurements conducted on plots with slope lengths of 72 feet at a 9% gradient.

\[ A = R \times LS \times K \times C \times P \]  
(Eq. 3)

\( A \) represents average annual soil loss per unit area, commonly expressed in tons/acre/year or tons/hectare/year.

\( R \) is the rainfall erosivity factor driven by raindrop impact forces and rill and interrill slope runoff. The \( R \) factor varies according to the intensity, duration, and frequency of rain events at a study area and is proportional to the Energy times Intensity (EI) metric. EI expresses how the total energy of a storm is related to its peak intensity, capturing the detachment and runoff potential of rainstorms. \( R \) was first published in the USLE in an isoerodent map assigning \( R \) values for the contiguous United States (Wischmeier and Smith 1978). \( R \) is expressed in metric units of millijoules * mm/hectare/hour/year or US customary units of ft-tonf inches/acre/hour/year.

Wischmeier and Smith (1978) and Renard et. al. (1997) translated study plot observations and weather data into isolinear erosivity maps assigning \( R \) factors for the continental United States.

\( LS \) is the combined slope length and slope steepness variable, which is actually composed of two separate components. Originally, slope length and steepness were
recorded during field visits and a quadratic equation (Wischmeier and Smith 1978) was used to calculate the LS factor. The difficulty of obtaining precise slope length measurements often lead to the generalization of the L variable into a constant value for the study area (Rodriguez and Suarez 2010). Additionally, it was discovered that Wischmeier and Smith’s (1978) procedure for calculating L and S did not achieve acceptable results when applied to steep or complex slopes, especially on rangeland landscapes (Renard et al. 1997).

K, the soil erodability factor, describes the inherent susceptibility of soil types based on physical and chemical composition. Specifically, K is based on soil texture, structure, and permeability. The ubiquity of the USLE and related models has led to K values of soil types being recorded by Natural Resources Conservation Service (NRCS) soil surveys. K is expressed as the rate of soil loss per R unit relative to the USLE standard unit plot. Wischmeier and Smith (1978) described K as a function of particle size, percent organic matter, structure classification, and permeability class. Due to the popularity and portability of the USLE and RUSLE models, the K factor is published by the NRCS for each map unit defined in a soil survey. To account for the effect rock fragments have in reducing the erodability of the soil, two subfactors of K, Kf and Kw are provided for each soil map unit. Kf is recommended for use in measuring the erodability of fine sediments, and Kw takes into the account of rock fragments within the soil.

C accounts for the variation of land cover and land use. C is a unitless construct ranging from near zero to one or above, representing the relative impact management and cover factors have on soil loss. For example, higher amounts of vegetative land cover
inhibit sheet erosion by intercepting rain drops. Rill erosion is mitigated by the stabilizing effect of root structures, which reduce flow velocity and soil detachment. Conversely, lower amounts of cover and more intensive land uses result in higher overland flow velocities and fewer soil stabilization structures. In USLE, C is often calculated according to established values applied to vegetation or other land cover and land use classes, or derived from time-intensive field subfactor calculations (Renard et al. 1997).

P represents soil management practices. Areas where soil conservation measures have been implemented are denoted with smaller P-values, while areas receiving no support practices to mitigate erosion are assigned a P-value of 1.

Model Variation

All factors for the original USLE were revised and refined in Renard et al.’s (1997) Revised Universal Soil Loss Equation (RUSLE). In addition to estimating input factors and subsequent soil loss predictions with greater accuracy, the RUSLE was intended to increase the accuracy of soil loss predictions of non-agricultural areas. The R factor was revised using additional climate data and subsequent higher resolution isoerodent maps. Daly et al. (2004) standardized R factors by interpolating weather station data across the contiguous United States. The S factor was updated based on the work of McCool et al. (1987). Based on the assumption that soil loss increases more rapidly with increases in slope steepness than with increases in slope length, McCool et al. (1987) used two separate equations to calculate S based on a slope cutoff value of nine percent.
For slopes less than 9 percent:

\[ S = 10.8 \sin (\text{slope angle}) + 0.03 \]  
\[ \text{(Eq. 4)} \]

For slopes greater than or equal to 9 percent:

\[ S = 16.8 \sin (\text{slope angle}) - 0.50 \]

Based on a study in mountainous terrain, Nearing (1997) argued that the solution offered by McCool et al. (1987) under-predicts the slope factor for steep slopes above 22%. Nearing (1997) offered a continuous logistic function intended to closely resemble USLE and RUSLE estimates until the slope threshold is met where their accuracy declines. It is expressed as:

\[ S = -1.5 + 17 / [1 + \exp(2.3 - 6.1 \sin (\text{slope angle})] \]  
\[ \text{(Eq. 5)} \]

**The USLE and GIS**

Warren et al. (1989) pioneered the extension of the USLE into GIS using military training sites and Geographical Resources Analysis Support System (GRASS). Using this approach, the authors were able to generate soil loss predictions for military installations and identify areas which were receiving erosive impacts beyond their
tolerance capacity, and recommend mitigation strategies as appropriate. This study created a template for utilizing the USLE in a GIS environment.

With the transition to raster GIS implementations of USLE, methodologies have been developed to calculate the LS factor by performing spatial analysis on grid DEMs, facilitating the analysis of soil loss at landscape scales. Hickey (2000) developed an Arc Macro Language (AML) program to refine the way slope steepness, and especially slope length, are calculated from DEM data. While this approach reduces errors caused by slope length overestimation and increases the effective resolution of input elevation models, its implementation limited its longevity as AML programs are no longer supported by ArcGIS. Alternative raster calculations (Mitasova et al. 1996, Mitasova and Mitas 1999, and Fernandez et al. 2003) have proven effective at estimating the LS factor for complex slopes within raster-based implementations of USLE. Mitasova and Mitas (1999) combined this approach with ArcGIS Spatial Analyst and raster math functions to yield the following equation:

\[ S = \text{Pow}(\sin([\text{slope angle}] * 0.01745) / 0.09, 1.3)) \]  
(Eq. 6)

When used within a GIS, the concept of slope length has been largely replaced with metrics measuring upslope contributing area for each grid cell. This facilitates the analyses of complex topographic study areas such as watersheds and small catchments, whose variety of slope lengths are not feasible to measure comprehensively. This concept also more accurately models the way water flows downhill, capturing its tendency to converge in small rivulets and rills during rain events rather than flowing
across the slope as a uniform sheet. The equation commonly used for this is a direct adaptation of the RUSLE slope length equation recommended by Renard et al. (1997), the only distinction being that accumulated flow is replacing slope length.

\[
L = \text{Power}([\text{FlowAccumulation}([\text{FlowDirection(GRID ELEVATION)}]) * \left[\frac{\text{DEM resolution}}{72.6, 0.6}\right])}
\]

(Eq. 7)

In RUSLE, the C factor is calculated as the product of several subfactors: prior land use, canopy cover, surface cover, surface roughness, and soil moisture. These subfactors are among the most detailed and time-intensive calculations involved in the RUSLE. This makes calculation of the RUSLE C factor extremely difficult in landscape scale GIS studies, as the spatial variation of the four subfactors is difficult to ascertain reliably. As an alternative, several authors estimated the C factor using remote sensing technology. This method has the advantage of obtaining C factor estimates for entire watersheds and landscapes with minimal amounts of field work. The most common spectral index to use for estimating the C factor is the Normalized Difference Vegetation Index (NDVI). De Jong (1994 cited Van der Knijff et al. 1999) estimated the C factor using a linear least-squares method and the NDVI:

\[
C = 0.431 - .0805 * \text{NDVI}
\]

(Eq. 8)

In a study assessing erosion potential throughout the country of Italy, Van der Knijff et al. (1999) found that this linear approach tended to oversimplify land cover and
rescaled it to an exponential function using a comprehensive land cover database. Van
der Knijff et al. (1999) identified several shortcomings to this estimation methodology,
most related to the low spatial resolution of available input data. However, the authors
noted that they were able to obtain C factor estimates that correlated well with soil loss.
Van der Knijff et al. (1999) used the following equation:

\[ C = \exp[-2 \times \frac{\text{NDVI}}{1 - \text{NDVI}}] \]  
(Eq. 9)

Suriyaprsit and Shrestha (2008) used an alternative equation to derive C factors
from mountainous areas which would otherwise be inaccessible, plotting NDVI values
against canopy cover data collected in northern Thailand. Field verification of the C
factor estimates resulted in an efficiency of 0.77 using the exponential function:

\[ C = 0.227 \exp(-7.337 \times \text{NDVI}) \]  
(Eq. 10)

**Surface Modeling with Close-Range Digital Photogrammetry**

Extracting topographic information from aerial photographs has been in common
use since the early 20\textsuperscript{th} century, when analog stereo plotters were used in measurement
and drafting operations. The capabilities and efficiency of aerial photography were
greatly enhanced by the development of computer-assisted analytical photogrammetry in
the 1950s (Madin 2001).

The science of photogrammetry was further advanced with the transition to digital
photography, which employs advanced iterative computer algorithms to calculate the 3-D
position of features in overlapping photographs using known information about camera and lens properties. Properly conducted digital photogrammetry projects are capable of producing 3-D models which rival laser scanning technology in accuracy at much lower software and hardware entry costs (Eos Systems 2012).

While commonly employed from aerial platforms, digital photogrammetry can also be effectively used for close-range and terrestrial applications. Nouwakpo et al. (2010) investigated the use of close-range photogrammetry to assess soil erosion using a 2m x 2m soil box and simulated rain events. In a direct comparison with laser scanning technology, the authors found that their implementation of digital photogrammetry did not produce a level of resolution equal to models derived from LiDAR scanning. However, the drastically lower cost of a photogrammetric approach combined with recent advancements in photogrammetric and camera calibration algorithms make it a suitable tool for field applications measuring erosion. The authors noted that obtaining accurate and precise control point coordinates holds the key to high-accuracy photogrammetric soil erosion surveys.

The increase in resolution that high-resolution modeling technologies are able to provide can affect accuracy of soil loss estimates. In a comparison of 10-meter, 5-meter, 3-meter, and 1 meter digital terrain models (DTMs) Moriera et al. (2011) found that the increased nuance provided by higher resolutions tended to represent complex slope profiles containing more flat or gradually sloped areas, resulting in lower-trending and ostensibly more accurate soil loss estimates.
Chapter 3: Conceptual Framework and Methodology

Description of Data Sources

This study drew from a variety of data sources in order to conduct analytical functions and provide cartographic supplementation to the figures in this text. Data used for input into the soil loss models other than elevation data were derived from widely available and authoritative sets in order to promote consistency with other studies.


These drawings are a product of a survey published in 1966, including a 2-foot contour interval derived from an aerial photogrammetric survey flown in 1965. The drawings also include survey control monumentation coordinates provided in project coordinates. Topographic information derived from these data was used to create high-resolution topographic input for the USLE. Prior to this project, the survey sheets were scanned and catalogued by the Western Archeological Conservation Center (WACC) Museum Services Division, a digital and material collections repository operated by the National Park Service in Tucson, Arizona. Unfortunately, due to past data management lapses, no project metadata beyond what is displayed on the sheet index and control diagram sheets is available. Figure 3 is an example of the survey sheets.
Figure 3: Example of 1966 topographic survey sheet


  Fort Bowie’s base data GIS library contains data sets commonly used for a variety of purposes, including planning, management, maintenance, research, and interpretation. Data from this library was used to supplement the cartographic figures in this thesis.


  This dataset contains vegetation and soil data collected as part of the Sonoran Desert Network’s Vital Signs monitoring program, including
vegetation line-intercept data, soil stability, and soil bulk density information.

  
  A comprehensive vegetation mapping effort was completed in 2008 at Fort Bowie to characterize the spatial extent of the present vegetation communities. The associated vegetation formation data was used to compare calculated C-factor values to those previously published.

- Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. Soil Survey Geographic (SSURGO) Database for Fort Bowie National Historic Site, Arizona, 2002
  
  The SSURGO soil database contains K values (USLE soil erodability factors) for soil survey areas.

  
  This imagery was used to calculate an NDVI image for use in deriving the USLE C-factor.

- Digital Globe pan-sharpened 4-Band Quickbird Scene, Fort Bowie National Historic Site (April 2005).
  
  Similar to the NAIP imagery, this Quickbird scene was used to calculate an NDVI index. This index was used to calculate a smoother NDVI image to reduce the effects of both spatial variability and temporal NDVI change.
Description of Methodology

The methodology for this project consisted of four major tasks: data preparation, soil loss model execution, photogrammetric topographic sampling, and analysis. Figure 4 presents a flowchart diagramming the methodology of this study.
Figure 4: Methodology flowchart

Phase 1: Data Preparation

Phase 1 consisted of the process steps necessary to convert the topographic information contained in the 1965 survey into formats compatible with modern GIS software. This involved the following tasks:

a. Georeferencing topographic survey sheets
The survey sheets containing legacy topographic information were scanned prior to the initiation of this project. Because the survey took place before the modern era of GIS systems, it was necessary to add georeferenced information to the scanned files. This was accomplished using the Georeferencing toolbar within ArcMap.

The sheets contain survey control points, complete with northing, easting, and elevation values in US survey feet, as well as a 200 x 200 foot grid, resulting in between 27 and 38 reference points per sheet. A point feature class was created in the NAD 27 Arizona State Plane coordinate system (US survey feet). A 200 x 200 foot grid was created to reference the grid line intersections from the survey sheets. A series of links was created tying these points and intersections on the raster sheets to the corresponding vector features. Figure 5 depicts the georeferencing scheme for sheet number thirteen.

Figure 5: Georeferencing schema of sheet thirteen
Following link creation, the geographic transformation providing the lowest RMSE was applied. In all cases, either a third order polynomial transformation or the “adjust” transformation provided the best results. The adjust transformation is designed to optimize for both global Least Squares Fit and local accuracy of control points using a combination of polynomial transformations and TIN interpolation (Esri 2013). Table 1 lists the RMSE values and reference link amounts for each survey sheet used in the study.

Table 1: Georeferencing RMSE table

<table>
<thead>
<tr>
<th>Sheet No</th>
<th>RMSE (ft)</th>
<th>Number of Links</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>0.05338</td>
<td>35</td>
</tr>
<tr>
<td>9</td>
<td>0.11732</td>
<td>34</td>
</tr>
<tr>
<td>10</td>
<td>0.10392</td>
<td>28</td>
</tr>
<tr>
<td>12</td>
<td>0.05155</td>
<td>38</td>
</tr>
<tr>
<td>13</td>
<td>0.03594</td>
<td>38</td>
</tr>
<tr>
<td>14</td>
<td>0.05167</td>
<td>37</td>
</tr>
<tr>
<td>15</td>
<td>0.11879</td>
<td>37</td>
</tr>
<tr>
<td>17</td>
<td>0.17255</td>
<td>35</td>
</tr>
<tr>
<td>18</td>
<td>0.13176</td>
<td>38</td>
</tr>
<tr>
<td>19</td>
<td>0.11062</td>
<td>33</td>
</tr>
<tr>
<td>20</td>
<td>0.04296</td>
<td>36</td>
</tr>
<tr>
<td>25</td>
<td>0.05599</td>
<td>32</td>
</tr>
<tr>
<td>26</td>
<td>0.07409</td>
<td>34</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSE:</td>
<td>0.08620 ft</td>
<td></td>
</tr>
</tbody>
</table>
b. Digitization of topographic contour lines and spot elevations

After the thirteen sheets used in this thesis had been georeferenced, the next task was to convert the raster topographic symbology to vector features which could be analyzed by GIS software. This was accomplished using Esri’s ArcScan, an ArcMap extension designed to facilitate the conversion of scanned raster documents into vector formats. ArcScan provides tools to clean “noise”, fill holes and breaks in line data, interactively edit the values of raster cells, as well as several alternative digitization methods. One avenue is to automatically digitize all raster features. This option initially appears to offer more efficiency, but ArcScan’s inability to distinguish between topographic contour lines and other linear map features such as roads, results in much time spent cleaning extraneous features and merging disconnected segments. The alternative is the use of the Raster Trace tool, which generates a vector centerline between the start and end points on a raster line interactively selected by the user on an image with a binary classification scheme applied. While breaks and intersections still contributed to the time necessary to complete this task, this approach proved to be more efficient than automatically digitizing all raster features contained on the sheets. In addition to the contour lines, points representing spot elevations such as high points and other surveyed points were digitized into a point feature class. Due to the time constraints, a subset of thirteen of the total thirty-six survey sheets were used in this project. These sheets were chosen because they cover an area of Fort Bowie containing both sensitive and important resources (Hubbard et al. 2010) as well as previously identified areas of substantial soil erosion (Nauman Geospatial LLC 2010). Figure 6 presents the vector data extracted from the raster topographic survey sheets.
c. Elevation modeling

The contour lines resulting from the digitization process were encoded with elevation values contained on the survey sheets. Prior to this process, lines from adjacent sheets were connected and merged to create a seamless topographic contour data set. This reduced the amount of data entry necessary to attribute each feature. A digital elevation model was created using the ArcGIS Spatial Analyst “Topo to Raster” tool using the attributed contour lines, control points, and spot elevation measurements from the survey sheets. “Topo to Raster” is a set of interpolation algorithms that generate
hydrologically correct DEMs using the ANUDEM method from a variety of vector input data representing terrain features (Hutchinson 1988). Figure 7 presents a three dimensional view of the digitized contour data and resulting digital elevation model for sheet fourteen. To ensure adequate resolution of analysis and simplify conversion processes from mass change to vertical change, the DEM was created at a resolution of one foot. Figure 7 is a perspective view of the resultant elevation model.

Figure 7: 2.5 dimension perspective view of survey sheet fourteen
Phase 2: Soil Loss Modeling

The USLE soil loss model was processed using the spatial analysis capabilities within ArcMap. As described in the Chapter 2, the R, K, L and P factors (rainfall erosivity, soil erodability, slope length, and soil conservation support practice, respectively) were held constant while the S and C factors (topography and land cover) vary. This approach was chosen because several alternate methodologies have been used in GIS studies for calculating topographic and land cover factors, while the other factors are either standardized or not applicable to this study. The R and K factors are published in authoritative data sets for the contiguous United States (PRISM United States Mean Annual R-factor, 1971-2000 and NRCS SSURGO database, respectively). The P factor is essentially irrelevant for areas receiving no support practices.

a. R Factor

This study used mean annual R factor data sets produced by the PRISM Climate Group. These data were produced using the Parameter-elevation Regressions on Independent Slopes Model (PRISM), an advanced interpolation technique combining precipitation data at 1,842 stations in the years between 1971 and 2000, a mean annual precipitation raster to serve as a prediction raster, and digital elevation models (Daly et al. 1994). Figure 8 presents the PRISM R factor raster in the vicinity of the study area.
The PRISM R factor grid was interpolated at a cell size of four kilometers, which is a coarse resolution for many landscape scale soil erosion studies. According to the associated metadata, each cell value represents an average value distributed throughout the cell (Taylor 2002). Unless the unlikely scenario exists that there is a weather station located in extreme proximity to the study area, this is the best method to use because the interpolation considers the effects of topography on rainfall patterns as well as weather station data (Daly 2004). To estimate R more appropriately, cell centroids near the study area were converted to points. Then, a new raster surface was interpolated between the points at a cell size of fifty feet using Natural Neighbors interpolation. Figure 9 presents the results of this interpolation.
b. The L and S Factors

The L factor in this study was held constant using the upslope contributing area method (Equation 7) which is recommended for raster implementations of USLE, especially for complex terrain (Rodriguez and Suarez 2010). Figure 10 shows the results of the L factor calculation.
The one-foot resolution DEM produced from the digitized 1965 survey data was used to calculate the S factor using raster calculations based on equations 4, 5, and 6. Figure 11 contains the results of the various S factor equations and the raster calculator expressions used to generate them. As seen in Figure 11 and Table 2, the results of the S factor calculations show considerable variation. McCool et al. (1987) produced the lowest-trending estimate, perhaps because of the separate equation used to calculate slopes greater than 9%, which is a considerable portion of the mountainous study area. However, the higher maximum value for McCool et al. (1987) indicates that the curve of Nearing (1997) is eventually overtaken.
Figure 11: S factor calculation variants

S Factor Variants

- Mitasova and Mitas 1999
  \[ \text{Power}(\sin(\text{degree slope}) \times 0.01745 / 0.09, 1.3)) \]

- McCool et al. 1987
  \[
  \text{Cond}(\text{degree slope} < 5.14, \sin(\text{radian slope}) \times 10.8 + .03, \\
  \sin(\text{radian slope}) \times 10.4 - .5)
  \]

- Nearing 1997
  \[
  -1.5 + 17(1 + \exp(2.3 - 6.1 \times \sin(\text{radian slope})))
  \]

Cartography by Jacob DeGraayner
Table 2: S factor statistics

<table>
<thead>
<tr>
<th></th>
<th>McCool et al. 1987</th>
<th>Mitasova and Mitas 1999</th>
<th>Nearing 1997</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>15.566</td>
<td>21.590</td>
<td>15.010</td>
</tr>
<tr>
<td>Mean</td>
<td>4.368</td>
<td>4.800</td>
<td>5.080</td>
</tr>
<tr>
<td>Std. Deviation</td>
<td>2.302</td>
<td>2.850</td>
<td>3.070</td>
</tr>
</tbody>
</table>

c. K Factor

An NRCS soil survey (2002) identified two soil map units within the study area: Mabray and Atascosa-Chiricahua (Figure 12). Since none of the three C factor calculation methodologies used in this study take into account the effect of rock fragments within the soil, this study uses the Kw subfactor. Figure 12 maps the two soil map units present at the study area with their respective Kf and Kw subfactors. To prepare these data for analysis, the spatial and tabular data obtained from the NRCS were joined and converted to raster values in a cell size and extent consistent with the rest of the project data.
Figure 12: NRCS soil survey map units and K factors

d. C factor

The use of the NDVI index to calculate the C factor assumes a direct relationship between vegetation abundance as measured by NDVI and erosion impedance. In reality, there is almost certainly divergence from this relationship regardless of the methodology used to link the C factor to NDVI. However, this approach provides for much more spatial nuance at fine scales than assuming a constant C factor for entire plant communities, especially in communities with highly variable amounts of vegetative cover.

The C factor was variously calculated by the linear least squares method developed by De Jong (1994, Equation 8), the exponential function of Van der Knijff *et al.* (1997, Equation 9), and Equation 10 (Suriyaprasit and Shrestha 2008). Because no
data exist with which to reliably estimate the C-factor in prior years, this study assumes that land cover has remained constant over time. Although advanced process-based soil loss models do attempt to account for plant growth, the assumption of constant vegetation amounts is something most resource managers must make when simulating future events. In order to minimize the effect of short-term temporal variation as much as possible, NDVI indices from two data sources were averaged to produce a composite NDVI image. The first is a 2010 National Aerial Imagery program (NAIP) 4-band aerial orthoimagery product at a resolution of one meter. The second is a 4-band Quickbird scene taken in April of 2005 and pan-sharpened to a resolution of 60 centimeters.

Both images were projected to the project coordinate system and resampled to the resolution of the other USLE raster input data. Then, an NDVI for each image was calculated, and the values from each raster were added and divided by two to create an average NDVI dataset. In order to reduce noise caused by registration mismatch between the two images, a 3 x 3 low-pass filter was applied to smooth the final NDVI image. Figure 13 presents the two 4-band images and the resultant averaged NDVI raster.

Following the calculation of the averaged NDVI index, the C factor was calculated according to the three methodologies described by De Jong (1994), Van der Knijff et al. (1999) and Suriyaprasit and Shrestha (2008). Figure 14 presents the results of the calculations. As noted in Table 3, the results vary considerably. The numbers yielded by De Jong (1994) and Van der Knijff et al. (1999) are higher than those published by Wischmeier and Smith (1978). This is partly due to the fact that NDVI is not highly sensitive to the differences between bare earth and rocky soil. However, this is addressed
by the use of the RUSLE Kw factor instead of Kf, which take into account the decreased susceptibility to erosion of rocky soil.

Figure 13: NAIP, Quickbird, and final NDVI images
Figure 14: USLE C factor variants
Table 3: C factor statistics

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>0.451</td>
<td>1.479</td>
<td>1.355</td>
</tr>
<tr>
<td>Mean</td>
<td>0.416</td>
<td>0.649</td>
<td>0.069</td>
</tr>
<tr>
<td>Std. Deviation</td>
<td>0.001</td>
<td>0.014</td>
<td>0.032</td>
</tr>
</tbody>
</table>

Model Calculation

After the individual factor variants had been calculated, the R, K, LS, and C factors were combined to generate annual soil loss predictions for the study area. To this end, an ArcGIS Modelbuilder model was created to automate the process. The cartographic results of the nine variant combinations of the S and C factors can be found in Appendix A. These data are stretched by 1 standard deviation in order to mitigate the influence of extremely high and extremely low values which otherwise diminish the impression of variation among sample site areas. Likewise, the total loss statistics can be misleading. One reason for this is the presence of highly concentrated stream channels which receive flow accumulation from entire watersheds. Not only is the USLE not designed to estimate loss in channels such as this (Mitasa and Mitas 1999), but the majority of established channels consist of a bedrock flowline, and thus only participate in sediment transport rather than detachment.

In order to convert the annual soil loss estimates into terms of expected topographic change, two steps were taken: the annual estimates were aggregated to simulate 48 years of erosion, and the units were converted from mass to expected vertical change. This latter task was accomplished using the bulk density metrics published in the NRCS soil survey (NRCS Soil Survey Staff 2002). The average field bulk density of the
Mabray soil map unit is listed at 1.3 grams per cubic centimeter. The average bulk density of the Atascosa-Chiricahua soil complex is listed at 1.55 grams per cubic centimeter. Vertical topographic change as a function of mass lost can be thought of in terms of cubic feet of volume lost per square foot of surface. Therefore, grams per cubic centimeter were converted to cubic feet per ton. This figure divided by the square feet per acre (43,560) yields vertical change in feet per acre per ton per year. A raster dataset was created for each soil map unit, and multiplied by the nine annual soil loss estimate variants times 48, the number of years that have elapsed between the 1965 survey and 2013.

Phase 3: 2013 Topographic Sampling

The next phase of the project was to collect data with which to compare current topographic conditions at Fort Bowie NHS with the topographic survey data collected in 1965. This was accomplished using a terrestrial (ground based) digital close-range photogrammetric survey of five sample sites within the study area. This phase consists of two separate tasks: field work and post-processing of the photogrammetric models.

Prior to field work, several possible sampling areas were considered for sampling based on the following criteria:

- Sufficient slope: Some degree of slope is necessary for creating photogrammetric models due to the terrestrial nature of the survey. Areas with little or no slope are not conducive to sampling with this technique because of the difficulty of capturing both ground surface and
photogrammetric targets in a sufficient amount of properly taken photographs. Secondly, one of the goals of this project was to compare erosion predictions using sites that were experiencing measurable levels of soil loss, which is much more likely to occur on sloping hillsides.

- Manageable vegetation levels: Dense vegetation obscures the ground surface and makes obtaining ground measurement models difficult. See Chapter 4 for a discussion of the effect of vegetation on this type of survey.

- Proximity to ground control points. In order to reference the photogrammetric models in the same coordinate system as the 1965 survey, the physical ground control used must be visible from the total station setup in order to calculate the coordinates of the photogrammetric targets. Due to the amount of time passed between 1965 and the present, it was not possible to know how many, if any, of the control points still existed at their installed location.

The first task of the field portion of this project was to ground-truth control points and select sampling sites based on the above criteria. Of the sixteen control monuments that an attempt was made to relocate, nine were relocated successfully in situ, three were relocated but damaged enough to prevent use, and five were not relocated. Two of the relocated monuments had been buried by a layer of soil deposition but were successfully relocated using a metal detector (Figure 15).
Figure 15: Damaged control monument (left) and buried control monument (right)

Five sites were selected for sampling (Figure 16), although several sampling sites involved multiple target setups and several individual photogrammetry projects. At each sample site, the following procedure was followed:

The electronic theodolite (total station) was installed below the target hillslope, within view of two relocated survey control monuments. While a total station such as the Topcon GPT-2003 used for this project is capable of measuring angles and distances with great accuracy, it requires input information to solve for its position and orientation in space. There are several survey methods which can be used to provide this information. The most commonly used is to install the instrument above a known point and measure the horizontal azimuth to at least one other known point, called a backsight. This allows the instrument’s relative circle reading to be referenced to that of the control coordinate system. An alternative method is called a resection. When using a resection, the distance and vertical and horizontal azimuths to at least two known points are measured, allowing the position and orientation of the instrument to
be triangulated. This method has the advantage of allowing the user to install the instrument at an unknown point from which the area of survey may be more visible. Because of this advantage, the resection method was chosen for all site setups in this survey. In order to maximize the accuracy of the setup location, and by extension, the target locations, several readings of each visible control point were taken with the instrument scope in normal position and reversed, and then averaged to compute the instrument location. The standard error measurements for each total station setup are listed in Table 4.

Table 4: Standard error values for total station setups (ft)

<table>
<thead>
<tr>
<th>Instrument Setup</th>
<th>Northing</th>
<th>Easting</th>
<th>Elevation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.051</td>
<td>0.03</td>
<td>0.008</td>
</tr>
<tr>
<td>2</td>
<td>0.007</td>
<td>0.003</td>
<td>0.058</td>
</tr>
<tr>
<td>3</td>
<td>0.015</td>
<td>0.06</td>
<td>0.006</td>
</tr>
<tr>
<td>4</td>
<td>0.008</td>
<td>0.048</td>
<td>0.005</td>
</tr>
<tr>
<td>5</td>
<td>0.0035</td>
<td>0.03058</td>
<td>0.016</td>
</tr>
</tbody>
</table>
Figure 16: Sampling locations and total station resections
Eight custom targets were distributed throughout each sample site. These targets were designed to be positioned very accurately by both the total station and the photogrammetric processing package. They consisted of a large black ring roughly two feet in diameter on white, cardboard-backed paper. This circular, high-contrast design was to allow Photomodeler Scanner to use the ring to mark the center of the target on photographs with sub-pixel accuracy. A highly retro-reflective target was adhered to the center of the ring to allow measurements of the target locations using the reflectorless mode. This allowed accurate measurements beyond the quoted range for measurements without a prism. Northing, easting, and elevation values were recorded for each target’s location at a sample site. Figure 17 depicts the site setup at sample site #1.

Figure 17: Site setup at sample site #1 showing total station (foreground) and targets (background)
A series of photographs were taken according to photogrammetric best practices for three-dimensional modeling. Digital photogrammetry is based on software algorithms which identify common objects on multiple photographs. The greater the amount of photographs which contain a given object, the more accurately the location of the object can be determined in three-dimensional space. Therefore, a large degree of photo overlap is desirable, and it is especially important to take many photos containing target points to accurately reference their positions. Several camera considerations are important as well. This project used a Canon 7D DSLR with an eighteen megapixel sensor and a 28mm prime wide-angle lens. A constant manual focus was used to avoid changes in focal distance, which can introduce uncertainty into the solution. The “aperture priority” setting was used in order to maintain a small aperture. This helped increase depth-of-field, the portion of the photograph which is in sharp focus. Finally, a mix of standard photos and photos “rolled” ninety degrees were included to facilitate a field calibration in post processing for refined camera and lens parameters.

The field photographs were processed using Photomodeler Scanner (EOS Systems 2012). The first order of business when processing a photogrammetric model in Photomodeler Scanner is to solve for the position and orientation of the camera sensor when each photo was taken. This can be accomplished in several ways. Easily identified points can be referenced across multiple photos by the software user. When using this method, accuracy is limited by the user’s ability to place the points accurately. A second method is to use coded targets in the photographs, which Photomodeler can identify and mark automatically. This method has the benefit of being the most accurate. However, placing adequate targets throughout the study area limits the scope of projects it can be
used for. A third method, referred to as SmartMatch in Photomodeler, samples each photograph to identify common points based on pixel characteristics. Because of the ability to reference very large numbers of points, SmartMatch is another way to achieve high accuracy in appropriate projects. SmartMatch relies on a relatively high degree of textural contrast to identify common points across photographs and thus is unsuitable for use when modeling smooth, uniform surfaces. However, for high-contrast subjects such as soil and vegetation, SmartMatch is an effective solution for accurate photo orientation.

Once the set of photos was oriented, the center of each target was marked in each photo which it appeared. When possible, this was mostly accomplished using Photomodeler’s sub-pixel target marking capability. Using this tool, the software searches a region of interest defined by the user for a high-contrast circular object and calculates the center point of the circle. Figure 18 shows an example of a target marked using this method.
After the targets in each photo project were marked, the default coordinate system in the photogrammetry projects was converted to project coordinates by assigning the total station measurements to the marked target points. This applied a linear Helmert transformation to the project, fitting the coordinates of the photogrammetric solution to the control data without altering the dimensional proportions. Because of this, any transformation will retain residual values that can be used to assess the accuracy of the photogrammetric project relative to the control data by comparing the location of a target point in the model to its measured location. In some instances target points were removed from a solution if they introduced a substantial amount of error in to the solution. These instances were likely caused by a target moving in a gust of wind between the total station measurement and the photography, or vegetation obscuring a target in too many photographs. Tables expressing the quality of each photogrammetry project in terms of target point residuals can be found in Appendix B. In some cases, the
photography at a particular site resulted in two sets of photogrammetric models which did not share sufficient reference points to be combined into one model. These projects are identified with lower case Arabic numbers following the site number (e.g. “photogrammetry project 2a”) in Appendix B.

Prior to the project, the camera was calibrated in an office setting. The goal of calibration is to accurately approximate the camera’s internal parameters. For example, calibration of the camera used in this project calculated the focal length of the lens as 29.03 millimeters rather than the published 28 millimeters. Accurate estimation of these parameters allows the software to use actual numbers from within the camera rather than reported approximation when correcting for factors such as lens distortion. However, for projects involving subjects at substantially different distances, a field calibration can increase project accuracy by recalculating parameter estimates for the distance ranges used. In order to successfully conduct a field calibration, all photos must have a high number of shared points. In addition, several photos “rolled” ninety degrees must be incorporated for the software to compare point locations on different areas of the lens.

After each photogrammetric model had been oriented, marked, georeferenced, and field calibrated, digital surface models (DSMs) were generated from stereo pair photographs to create surface models of areas within the sample sites. Digital close-range photogrammetry is only capable of creating digital surface models (DSMs) rather than digital terrain models (DTMs) because of the modeling of objects which occur above the earth surface. The most common of these objects are vegetation, which was excluded from modeling using multiple techniques. One method of vegetation exclusion was accomplished by defining area of interest boundaries (known as DSM trims in
Photomodeler scanner) in two or more photographs that encompassed an area of relatively bare ground, and creating a DSM limited to the area that lay within these trims on both photographs in the stereo pair. This process was repeated until the maximum amount of bare earth surface was modeled for each project area. The suitability of a pair of photographs for creating a DSM depends largely on three factors: a minimum number of shared and well-distributed reference points, a base-to-height ratio within an acceptable range to ensure sufficient overlap, and a low angle between the photos to maintain a degree of similarity between images. In Photomodeler Scanner, a base-to-height ratio of between 0.1 and 0.5 is recommended, meaning that the distance between where the two images were taken is between 10% and 50% of the distance to the subject surface being modeled. Figure 19 depicts a stereo pair in post-processing with a base-to-height ratio of approximately 0.11.

Figure 19: Processing a stereo pair from Site 3 in Photomodeler Scanner
Following the DSM process, the resultant point clouds were interactively edited to remove vegetation noise and visibly erroneous noise points. While the majority of vegetation points are easy to identify and remove based on their position relative to the ground surface and RGB values, it is certain that all vegetation was not removed in all cases, especially where short, seasonally dormant, earth-colored grasses and forbs were difficult to distinguish from bare-earth surface. This might not be problematic for many photogrammetric modeling applications, but vegetation likely contributed a small systematic bias toward higher topographic values, and by extension, lower topographic change estimates, in this study due to the close vertical tolerances involved. This bias is difficult to quantify, but likely does not exceed a few centimeters.

Phase 4: Model Evaluation

The CADD format point files exported from Photomodeler Scanner were converted into ESRI geodatabase point feature classes. Then, they were overlaid onto the DEM interpolated from the 1965 survey data, and raster values were extracted using a Spatial Analyst function. A field was calculated in each feature class representing the difference between the point elevation as measured in 2013 and the DEM. Then, the point feature classes were converted to raster datasets at the same resolution as the nine soil loss estimates for analysis. This step was completed in order to average values from the dense surface points over each prediction raster cell and also resulted in much more manageable file sizes for analysis.
Measured soil losses were compared to model predictions in three phases. The first was the individual cell level, to attempt to extract information regarding model performance at the smallest spatial scale. The second method expanded the analysis to the sampling site level to gauge model performance at the larger slope and sub-catchment scale. The thirdly, the predictions and measurements were aggregated to slope units consisting of individual topographic features. These units were intended to resemble the original USLE unit plots. The assessment of model performance at varying spatial scales was intended to provide insight into the proper scales for undertaking soil loss predictions using these models. Finally, the slope and land cover parameters varied in this study were examined individually to assess their role in model accuracy.
Chapter 4: Analysis Results and Discussion

Cell Level Analysis

The next analysis task was to examine the relationships between model prediction and soil loss measurements at the individual cell level. The advantage of analysis at this spatial scale is the large number of observations available to test. To this end, raster values from each soil loss variant were extracted using the terrain model cells as mask extents. As shown in Table 5, loss measurements showed weak correlation levels with all of the loss model variants.

Table 5: Cell level soil loss regression statistics

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>R Statistic</td>
<td>0.00510</td>
<td>0.00199</td>
<td>0.00105</td>
<td>0.02353</td>
<td>0.02007</td>
<td>0.01884</td>
<td>0.01784</td>
<td>0.01443</td>
<td>0.01338</td>
</tr>
<tr>
<td>R Square</td>
<td>0.000003</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.00055</td>
<td>0.00040</td>
<td>0.00035</td>
<td>0.00032</td>
<td>0.00021</td>
<td>0.00018</td>
</tr>
</tbody>
</table>

In order to investigate whether these results were being confused by depositional activity, regression analyses were run on absolute values of topographic change for all cells sampled. This method had a secondary objective to determine if any of the USLE variants could be used as indicators of both sources of topographic change, as both erosion and deposition are part of the same overall process both can exacerbate to resource concerns. Table 6 shows the results of the regressions on absolute value measurements.
Table 6: Cell level absolute value topographic change regression statistics

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>R Statistic</strong></td>
<td>0.0897</td>
<td>0.0921</td>
<td>0.0936</td>
<td>0.0903</td>
<td>0.0929</td>
<td>0.0944</td>
<td>0.0905</td>
<td>0.0930</td>
<td>0.0945</td>
</tr>
<tr>
<td><strong>R Square</strong></td>
<td>0.0081</td>
<td>0.0085</td>
<td>0.0088</td>
<td>0.0082</td>
<td>0.0086</td>
<td>0.0089</td>
<td>0.0082</td>
<td>0.0087</td>
<td>0.0089</td>
</tr>
</tbody>
</table>

The coefficients for absolute topographic change remained weak, but higher than for erosion only. Because higher, if still weak, levels of correlation were produced, there exists a possibility that the predictive utility of the soil loss models was at least partially being hampered by the effects of depositional activity at the cell level.

A principle assumption in the use of USLE-related models is that erosion is limited by detachment capacity rather than transport capacity – that all sediment detachment caused by raindrop impact or rill erosion will be removed from the site. The results of this study, as well as empirical site observations (Figure 15), demonstrate that this is not a valid assumption to make at this study area, even at relatively steep slopes with little vegetation that appear to be actively eroding. Mitasova et al. (1995) recommend the exclusion of depositional areas from raster-based USLE projects. It is difficult to obtain a priori knowledge of the spatial extent of erosion and deposition. In itself, this piece of information is a compelling argument that alternative loss models to the USLE be considered when attempting soil loss measurements. However, knowledge of model accuracy for eroding areas alone is a valuable tool in assessing relative rates of soil loss in study areas, although the precise spatial extent of erosion and deposition remains difficult to ascertain.

53
As a final step in the cell-level portion of the analysis, cells indicating depositional activity were excluded from the data and the regression analysis was repeated. As shown in Table 7, the exclusion of depositional cells resulted in higher correlation coefficients than analyses incorporating all cells or using absolute values of topographic change. R squared values remained low, fluctuating near 1%.

Table 7: Regression statistics on cell experiencing net erosion

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>R Statistic</td>
<td>0.1023</td>
<td>0.1040</td>
<td>0.1050</td>
<td>0.1044</td>
<td>0.1067</td>
<td>0.1076</td>
<td>0.1037</td>
<td>0.1059</td>
<td>0.1068</td>
</tr>
<tr>
<td>R Square</td>
<td>0.0105</td>
<td>0.0108</td>
<td>0.0110</td>
<td>0.0109</td>
<td>0.0114</td>
<td>0.0116</td>
<td>0.0108</td>
<td>0.0112</td>
<td>0.0114</td>
</tr>
</tbody>
</table>

Several reasons can be identified as likely causes contributing to low correlation levels when analysis is performed at this scale. First, loss estimates are highly dependent on flow accumulations involving the concentration of flow in small rills. The exact locations of these concentrations may not be accurately modeled by the input DEM and are likely to have shifted position over the course of the study time period. Treating each cell as independent of surrounding cells ignores the influence of micro-topographical change over time, as the topographic change experienced by a cell likely affects the erosion of its neighbors. Similarly, the growth or death of a single plant would be enough to alter the C factor of a specific pixel, even if the average C factor of a sampling site remained relatively constant.
Site Level Analysis

During the second phase of the analysis the terrain samples were compared with the soil loss estimates quantitatively in order to get a broad numeric picture of model performance at the five sampling sites. Summary statistics were calculated from the extracted rasters to evaluate the models in terms of net soil loss at each sampling site. As seen in Table 8 below, two of the five sampling sites experienced negative soil loss as a function of topographic change, or in other words, net deposition. To mirror the approach taken at the cell level, these depositional cells were excluded from further analysis.


<table>
<thead>
<tr>
<th>Net Topographic Change and USLE Variant Predictions</th>
<th>Site 1</th>
<th>Site 2</th>
<th>Site 3</th>
<th>Site 4</th>
<th>Site 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measured Net Soil Loss (ft³)</td>
<td>-452.28</td>
<td>1047.88</td>
<td>3007.94</td>
<td>17.60</td>
<td>-287.37</td>
</tr>
<tr>
<td>McCool <em>et al.</em> 1987, Suriyaprisit and Shreshta 2008</td>
<td>39.21</td>
<td>51.69</td>
<td>776.46</td>
<td>6.44</td>
<td>41.72</td>
</tr>
<tr>
<td>Mitasova and Mitas 1999, Suriyaprisit and Shrestha 2008</td>
<td>44.06</td>
<td>59.77</td>
<td>827.88</td>
<td>6.45</td>
<td>40.55</td>
</tr>
<tr>
<td>Nearing 1997, Suriyaprisit and Shrestha 2008</td>
<td>47.23</td>
<td>63.21</td>
<td>876.47</td>
<td>6.51</td>
<td>40.00</td>
</tr>
<tr>
<td>McCool <em>et al.</em> 1987, De Jong 1994</td>
<td>136.51</td>
<td>207.56</td>
<td>4017.79</td>
<td>26.82</td>
<td>183.79</td>
</tr>
<tr>
<td>Nearing 1997, De Jong 1999</td>
<td>164.42</td>
<td>254.00</td>
<td>4531.17</td>
<td>27.10</td>
<td>176.19</td>
</tr>
<tr>
<td>McCool <em>et al.</em> 1987, Van der Knijff <em>et al.</em> 1999</td>
<td>266.11</td>
<td>385.44</td>
<td>6874.07</td>
<td>49.44</td>
<td>332.56</td>
</tr>
<tr>
<td>Mitasova and Mitas 1999, Van der Knijff <em>et al.</em> 1999</td>
<td>299.05</td>
<td>466.60</td>
<td>7326.73</td>
<td>49.49</td>
<td>323.25</td>
</tr>
<tr>
<td>Nearing 1997, Van der Knijff <em>et al.</em> 1999</td>
<td>320.54</td>
<td>471.58</td>
<td>7755.22</td>
<td>49.98</td>
<td>318.83</td>
</tr>
</tbody>
</table>
Soil loss in terms of topographic change was aggregated and averaged by sample site and compared to the nine average loss predictions. Overall accuracy rank was somewhat driven by the C factor calculation method. Methods using Equation 9 (Van der Knijff et al. 1999) ranked first, second, and fourth, methods using De Jong’s (1994) equation occupied the third, fifth, and sixth places, while methods using Equation 10 (Suriyaprasit and Shrestha 2008) yielded the lowest amounts of agreement due to lower estimates (Figure 20, Table 9).

Table 9: Variant agreement on areas experiencing net erosion

<table>
<thead>
<tr>
<th>USLE Variant and Agreement Rank</th>
<th>Site 1</th>
<th>Site 2</th>
<th>Site 3</th>
<th>Site 4</th>
<th>Site 5</th>
<th>Agreement Score</th>
<th>Accuracy Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>McCool et al. 1987, Suriyaprasit and Shrestha 2008</td>
<td>9</td>
<td>9</td>
<td>8</td>
<td>9</td>
<td>7</td>
<td>42</td>
<td>9</td>
</tr>
<tr>
<td>Mitasova and Mitas 1999, Suriyaprasit and Shrestha 2008</td>
<td>8</td>
<td>8</td>
<td>6</td>
<td>9</td>
<td>8</td>
<td>39</td>
<td>8</td>
</tr>
<tr>
<td>Nearing 1997, Suriyaprasit and Shrestha 2008</td>
<td>7</td>
<td>7</td>
<td>5</td>
<td>7</td>
<td>9</td>
<td>35</td>
<td>7</td>
</tr>
<tr>
<td>McCool et al. 1999, De Jong 1994</td>
<td>3</td>
<td>6</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>17</td>
<td>3</td>
</tr>
<tr>
<td>Mitasova and Mitas 1999, De Jong 1994</td>
<td>5</td>
<td>5</td>
<td>2</td>
<td>4</td>
<td>5</td>
<td>21</td>
<td>5</td>
</tr>
<tr>
<td>Nearing 1997, De Jong 1994</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>6</td>
<td>6</td>
<td>23</td>
<td>6</td>
</tr>
<tr>
<td>McCool et al. 1987, Van der Knijff et al. 1999</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>1</td>
<td>2</td>
<td>13</td>
<td>1</td>
</tr>
<tr>
<td>Mitasova and Mitas 1999, Van der Knijff et al. 1999</td>
<td>2</td>
<td>2</td>
<td>7</td>
<td>3</td>
<td>4</td>
<td>18</td>
<td>4</td>
</tr>
<tr>
<td>Nearing 1997, Van der Knijff et al. 1999</td>
<td>1</td>
<td>1</td>
<td>9</td>
<td>2</td>
<td>1</td>
<td>14</td>
<td>2</td>
</tr>
</tbody>
</table>
Figure 20: Mean soil loss measurements and model variant predictions.
Slope Unit Analysis

Areas of erosion were divided into thirty-one slope units in order to analyze model performance at scales similar to the original USLE unit plot. The digital close-range photogrammetry naturally produced surface models in relatively distinct groups at each sample site due to the nature of the methodology and the availability of sampling surface. These units do not achieve the uniformity of slope and area as the original unit plots, but the area within is a relatively homogenous group of cells sharing the slope, aspect, and vegetation similarities of a distinct topographical feature. The extracted raster prediction and loss values were aggregated at each zone using the “Zonal Statistics as Table” Spatial Analyst function. This method allows the examination of model predictions and factor variation at scales similar to those at which the USLE was developed, as well as mitigating error introduced by the accuracy of the input data and temporal changes within each unit. These slope units are also at a spatial scale comparable to many archeological sites, so the assessment of soil loss predictions at these units would be of high relevance for resource management. The slope units are presented in Figure 21.
Measured soil losses at each erosion cell were aggregated into an average loss value for each slope unit and compared to each of the nine model variants. As with the analysis at the site level, prediction accuracy was ranked for each variant and totaled to derive an agreement score. These data are summarized in Table 10. In results analogous to the site-level analysis, variants using Equations 8 (De Jong 1994) and 9 (Van der Knijff *et al.* 1999) performed better relative to other loss variants. Variants using Equation 10 (Suriyaprasit and Shreshtha 2008) continued to yield estimates below measured losses.
Loss estimates were characterized by a high degree of fluctation from measured losses. Figure 22 compares the estimates of the three variants with the highest agreement rank with measured losses. The narrow range of Equation 8 (De Jong 1994) demonstrates that it is not as susceptible to large amounts of overestimation of soil loss at certain sites as Equation 9 (Van der Knijff et al. 1999), but also contributes to underestimations at sites experiencing high levels of erosion. Despite the high divergences of the estimates for measured losses, the trendlines fit by exponential smoothing do approximate the curve of measured losses to some degree, with Equation 8 (De Jong 1994) providing a more conservative trend. The functions imply that Equation 8 (De Jong 1994) provides more accurate results for lower levels of soil losses, while the exponential curve fit to Equation 9 (Van der Knijff et al. 1999) better approximates increased levels of loss. Figure 22 also suggests that cell aggregation accompanied by the application of functions such as exponential smoothing may be the most effective way to generate predictions less susceptible to the large fluctuations of the model predictions from measured losses when a similar methodology is employed.
Topographic factor discussion

In general, soil loss predictions from all variants were heavily correlated to the L factor. This was a surprising finding as the S component is often cited as the factor driving the sensitivity of soil loss (Renard *et al.* 1997). In regression analyses correlating the L factor and resultant prediction values, (Table 11), variance in the L factor was noted as driving between 74% and 80% of the variance within individual soil loss variants at the sample sites. The variance in the S factor, on the other hand, had much less effect on the estimates.
The dominance of the L factor in resultant loss estimates was at least partially due to its high fluctuation about a small mean. Cells containing nominal values of other USLE factors were highly influenced by an L-factor near zero or very high. Due to this important effect on loss estimates, further study should examine the use of upslope contributing area L factors with different DEM resolutions and interpolation techniques. Table 12 contains the coefficients of variance for the L factor and the three different S factor variants. The variance of L is likely related to the complexity of the study site. Uniformly sloped rectangular study plots, such as those the original USLE was developed with, can be expected to exhibit far less fluctuation of the L factor, leaving the slope inclination component as the most sensitive.
In terms of comparison between S factor calculation techniques, Equation 4 (McCool et al. 1987) trended below both Equation 5 (Nearing 1997) and Equation 6 (Mitasova and Mitas 1999). Except for a few areas exceeding the slope threshold where Equation 6 exceeds Equation 5, Equation 5 provided the highest S factor estimates in all cases. However, Figure 23 demonstrates that the other two equations overtake Equation 5 at very high slope angles. The mean slope at all areas sampled for this project was approximately nineteen degrees, so S factors using Equations 4, 5, and 6 resulted in relatively similar contributions to soil loss estimates.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>4.90882</td>
<td>5.66257</td>
<td>5.35840</td>
<td>0.76092</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>1.83284</td>
<td>2.54389</td>
<td>2.36811</td>
<td>1.12618</td>
</tr>
<tr>
<td>Coefficient of Variance</td>
<td>0.37338</td>
<td>0.44295</td>
<td>0.44194</td>
<td>1.48002</td>
</tr>
</tbody>
</table>
Cover Factor Discussion

As mentioned above, model agreement rank with mean soil losses at each site was heavily dependent on C factor calculation methodology. Equation 10 (Suriyaprasit and Shrestha 2008) C factor calculation technique provided the lowest estimates, while Equation 8 (De Jong 1994) and Equation 9 (Van der Knijff et al. 1999) were considerably higher. The L factor proved to be the primary factor influencing variation within models, while the C factor variants were the primary factor influencing variation between models.

Tables 13 and 14 compare C factor values from Equations 8, 9, and 10 to values commonly used for idle rangeland. Although Equation 10 (Suriyaprasit and Shrestha 2008) consistently under-predicted soil losses in this study, the values it produced are more comparable to the values published by Wischmeier and Smith (1978).
A possible explanation is the disturbed nature of the study area. In his assessment of erosion at Apache Springs watershed (where Sites 1 and 2 of this project are located), Nauman (2010) noted that many active erosional features were likely associated with soil and vegetation disturbance related to past military activity. Additionally, the study area was subject to light to moderate cattle grazing activity until 1998 (Fort Bowie Site Historian Larry Ludwig, personal communication, 8 April 2013). For highly disturbed, bare earth areas such as those associated with construction sites, a C factor of 1 is commonly applied (Israelson et al. 1980). The tendency of this study to agree with higher C factor values can be at least partially attributed toward the modeling of areas with low vegetative cover, as these areas were most suitable for terrestrial photogrammetric modeling. This is not a major drawback as these areas are naturally of most concern regarding soil erosion.

Table 13: Zonal C factor statistics aggregated by vegetation formations defined by Sonoran Desert Network 2008

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Shrubland</td>
<td>0.0827</td>
<td>0.4189</td>
<td>0.7052</td>
</tr>
<tr>
<td>Woodland</td>
<td>0.0631</td>
<td>0.4148</td>
<td>0.6106</td>
</tr>
<tr>
<td>Shrub Herbaceous</td>
<td>0.0627</td>
<td>0.4162</td>
<td>0.6391</td>
</tr>
<tr>
<td>Wooded Shrubland</td>
<td>0.0562</td>
<td>0.4144</td>
<td>0.5992</td>
</tr>
<tr>
<td>Forest and Woodland</td>
<td>0.0346</td>
<td>0.4070</td>
<td>0.4442</td>
</tr>
</tbody>
</table>
Table 14: C Factor table for permanent pasture, range, and idle land (Wischmeier and Smith 1978, p. 32)

<table>
<thead>
<tr>
<th>Vegetative canopy</th>
<th>Percent cover&lt;sup&gt;3&lt;/sup&gt;</th>
<th>Cover that contacts the soil surface</th>
<th>Percent ground cover&lt;sup&gt;4&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Type&lt;sup&gt;4&lt;/sup&gt;</td>
<td>0</td>
</tr>
<tr>
<td>No appreciable</td>
<td>G</td>
<td>0.45</td>
<td>0.20</td>
</tr>
<tr>
<td>canopy</td>
<td>W</td>
<td>0.45</td>
<td>0.24</td>
</tr>
<tr>
<td>Tall weeds or</td>
<td>G</td>
<td>0.36</td>
<td>0.17</td>
</tr>
<tr>
<td>short brush</td>
<td>W</td>
<td>0.36</td>
<td>0.20</td>
</tr>
<tr>
<td>with average</td>
<td>G</td>
<td>0.26</td>
<td>0.13</td>
</tr>
<tr>
<td>drop fall height</td>
<td>W</td>
<td>0.26</td>
<td>0.16</td>
</tr>
<tr>
<td>50</td>
<td></td>
<td>0.26</td>
<td>0.17</td>
</tr>
<tr>
<td>of 20 in</td>
<td></td>
<td>0.26</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.28</td>
<td>0.14</td>
</tr>
<tr>
<td>True appreciable</td>
<td>G</td>
<td>0.40</td>
<td>0.18</td>
</tr>
<tr>
<td>bush, with</td>
<td>W</td>
<td>0.40</td>
<td>0.22</td>
</tr>
<tr>
<td>average drop fall</td>
<td>G</td>
<td>0.34</td>
<td>0.16</td>
</tr>
<tr>
<td>height of 6½ ft</td>
<td>W</td>
<td>0.34</td>
<td>0.19</td>
</tr>
<tr>
<td>50</td>
<td></td>
<td>0.28</td>
<td>0.14</td>
</tr>
<tr>
<td>of 13 ft</td>
<td></td>
<td>0.28</td>
<td>0.17</td>
</tr>
<tr>
<td>Trees, but no</td>
<td>G</td>
<td>0.42</td>
<td>0.19</td>
</tr>
<tr>
<td>appreciable low</td>
<td>W</td>
<td>0.42</td>
<td>0.23</td>
</tr>
<tr>
<td>brush. Average</td>
<td></td>
<td>0.39</td>
<td>0.18</td>
</tr>
<tr>
<td>drop fall height</td>
<td>G</td>
<td>0.39</td>
<td>0.21</td>
</tr>
<tr>
<td>50</td>
<td>W</td>
<td>0.39</td>
<td>0.21</td>
</tr>
<tr>
<td>of 13 ft</td>
<td></td>
<td>0.36</td>
<td>0.17</td>
</tr>
<tr>
<td>75</td>
<td>W</td>
<td>0.36</td>
<td>0.20</td>
</tr>
</tbody>
</table>
The results suggest that Equation 9 (Van der Knijff *et al*. 1999) may be scaled more appropriately for estimating soil loss on bare or disturbed ground from NDVI data. The results of Equation 8 (De Jong 1994) resemble some values associated with low land cover, but the calculation technique resulted in a narrow band of values that is not likely to capture the diversity of cover and management at most study areas. For example, a sparse shrubland with much open ground would normally be expected to experience many times the potential soil loss than a forest with near 100 percent canopy cover, other factors being equal. The limited range of Equation 8 (De Jong 1994) was less prone to overestimation than Equation 9.

In a regression analysis of the three C factor calculation methodologies, Equation 10 (Suriyaprasit and Shrestha 2008) displayed superior, albeit modest, correlation metrics than Equations 8 and 9 (Table 15). This suggests that Equation 10 could contribute to superior soil loss estimates if coefficients were scaled according to study area conditions. As noted by Van der Knijff *et al*. (1999) and Suriyaprasit and Shrestha (2008), the NDVI is not optimally suited for discerning detailed study area characteristics such as disturbance level, which can be problematic when attempting a USLE-related study using remotely sensed information. One avenue to address this shortcoming could be the use of ancillary data to aid in determination of the disturbance level and the subsequent C factor calculation technique, such as grazing records and site histories.
Table 15: Regression statistics comparing C factor variants and soil loss

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>R statistic</td>
<td>0.2269</td>
<td>0.2080</td>
<td>0.2092</td>
</tr>
<tr>
<td>R squared</td>
<td>0.0515</td>
<td>0.0433</td>
<td>0.0438</td>
</tr>
</tbody>
</table>
Chapter 5: Conclusion

This study used varying methodologies for calculating the USLE S and C factors using remotely sensed data and attempted to evaluate their suitability using a comparison between a 1965 topographic survey and 2013 site conditions using digital close-range photogrammetry. Photogrammetric models were referenced to the project coordinate system using reflective targets measured using an electronic theodolite. The 2013 survey sampled approximately 14,000 square feet at five sites within the study area, finding a mean vertical decrease of approximately 0.24 feet and net soil loss of approximately 3,333 cubic feet. With the exception of one sample site, measured soil losses exceeded model predictions. The overall goal of the study was to ascertain which combination of remotely sensed variants would give the most accurate estimates of occurring soil loss, thus identifying a methodology to use in future studies.

Because model agreement depended heavily on the choice of the C factor calculation technique, this study concludes that this is the most important decision to make when undertaking an erosion assessment project. Of the three methods evaluated, Suriyaprasit and Shrestha (2008) provided the closest estimates to published values, but fell far short of accounting for measured soil losses. De Jong’s (1994) method provided reasonable estimates for some study sites and correlated most closely with analysis at the slope unit level, but the simplicity of the equation resulted in a C factor range which would not adequately represent the diversity of land cover and associated erosional inhibition at most non-agricultural study areas. At the slope unit level, Equation 8 (De Jong 1994) was less likely to overestimate soil loss than Equation 9 (Van der Knijff et al.
which provided high estimates which most closely matched measured losses at four of five sampling sites, but also displayed a tendency to overestimate losses at several slope units. A possible explanation for this finding is the history of soil disturbance in the watersheds sampled due to historic military activity and grazing. The ideal solution would be to attempt to fit either Equation 10 (Suriyaprasit and Shrestha 2008) or Equation 9 (Van der Knijff et al. 1999) to measured loss data by modifying exponents to suit the conditions of the study area.

Three variants used to calculate the $S$, or slope inclination component of the topographic factor, were tested as well. Equations published by McCool et al. (1987), Nearing (1997), and Mitasova and Mitas (1999) provided relatively similar estimates at most slopes sampled in this study. This study found that the $L$ factor, which was held as a constant for all model variants, was heavily responsible for estimate fluctuation within each model variant, and should be evaluated further to investigate the relationships between input DEM resolution and interpolation techniques and resultant $L$ factors.

Several issues were encountered over the course of this research which posed challenges to the study. From the outset, positional error was identified as a challenge due to the multiple sources of propagation, from original error associated with the 1965 survey, georeferencing error when converting the survey sheets into a DEM, positional error associated with total station measurements, and residuals encountered when fitting the photogrammetric models to the project coordinate system. As seen in Tables 1 and 4, as well as Appendix B, efforts to quantify and minimize positional uncertainty were relatively successful. Since no supporting documentation was available for the 1965 topographic survey beyond the control network schema, error was assumed to form a
random distribution rather than systematic bias. Due to this assumption, it is difficult to draw conclusions from this study beyond identifying which calculation combinations were in closest agreement with loss as measured. The ideal continuation of this study would involve the comparison of topographic data from two time periods using identical methodologies to minimize conversion errors.

Vegetation levels at the sample sites also posed challenges for capturing field data. In addition to obscuring ground surface for modeling, vegetation in close proximity to the camera positions also increased the amount of heterogeneity between photographs in a project, making automated photographic orientation more difficult. As a result, the amount of ground surface able to be sampled in this study was less than originally planned. Although these issues are at least partially related to the nature of terrestrial photogrammetry, the shift to an oblique perspective does allow the modeling of some ground surface that is not visible from aerial platforms, such as areas beneath vegetation canopies. Digital close-range photogrammetry has been demonstrated as a viable approach for modeling ground surfaces, but it can be thought of as best suited for low vegetation areas where relatively orthogonal vantage points can be obtained from where to take photographs. For example, more surface area was modeled for Site 3 (see Appendix B for map) because photographs were taken from the opposite site of a relatively steep canyon. On the other hand, less area was obtainable for Site 5 because the photographs were taken from a flat area beneath the slope, resulting in a smaller angle of incidence from the camera to the surface. These considerations are of less concern for applications seeking to model general topography rather than extract surface measurements of high accuracy.
Alternate remote sensing technologies can be considered in order to monitor topographic change. Terrestrial laser scanning is one methodology capable of gathering large and detailed terrain datasets. However, the user would be likewise faced with the problem of removing vegetation noise, which would be a time-intensive and difficult task without automated algorithms capable of distinguishing ground surface from vegetation. The discrete return capability of airborne LiDAR sensors could address this problem effectively. However, the RMSE of aerial LiDAR flights is commonly no better than 12.5 centimeters, with increased accuracy being accompanied by considerable cost increases (USGS 2010). The most effective method in terms of accuracy and cost may still be conventional terrestrial survey techniques.

Perhaps the greatest challenge to this type of study lies in the pace of geomorphological processes. Even over the course of 48 years of monsoon rain events, soil losses were relatively modest in terms of topographic change. A comprehensive study at the requisite level of accuracy would require a large amount of expense distributed over a long temporal period and sufficient programmatic stability to allow for a long-term monitoring regime.

Although none of the soil loss models performed with great accuracy at all sampling sites, the study was successful in identifying calculation methodologies which could yield useful approximations of erosional activity exclusively through the use of remotely sensed data. In conclusion, De Jong’s equation (Equation 8 cited in Van der Knijff et al. 1999) in combination with any of the three S factors provided the most reasonable loss estimates in this study, although the narrow range of values would likely pose problems for a study involving a greater degree of variation among land cover.
Equation 9, (Van der Knijff et al. 1999) displayed a tendency for substantial overestimation at several slope units, although it did achieve the closest estimates for four of the five sites when analysis was conducted at a slightly larger scale.
Appendix A: USLE Variant Annual Soil Loss Maps

Figure 25: Estimated annual soil loss using McCool et al. (1987) and De Jong (1994)
Figure 26: Estimated annual soil loss using McCool et al. (1987) and Suriyprasit and Shrestha (2008)
Figure 27: Estimated annual soil loss using McCool et al. (1987) and Van der Knijff et al. (1999)
Figure 28: Estimated annual soil loss using Mitasova and Mitas (1999) and De Jong (1994)
Figure 29: Estimated annual soil loss using Mitasova and Mitas (1999) and Suriyaprasit and Shrestha (2008)
Figure 30: Estimated annual soil loss using Mitasova and Mitas (1999) and Van der Knijff et al. (1999)
Figure 31: Estimated annual soil loss using Nearing (1997) and De Jong (1994)
Figure 32: Estimated annual soil loss using Nearing (1997) Suriyaprasit and Shrestha (2008)
Figure 33: Estimated annual soil loss using Nearing (1997) and Van der Knijff et al. (1999)
Appendix B: Photogrammetry Project Maps and Quality Tables

Figure 34: Sample site 1 project overview

Table 16: Sample site 1 photogrammetry project quality

<table>
<thead>
<tr>
<th>Id</th>
<th>Model Point X</th>
<th>Model Point Y</th>
<th>Model Point Z</th>
<th>Check Point X</th>
<th>Check Point Y</th>
<th>Check Point Z</th>
<th>3D Distance</th>
<th>Delta X</th>
<th>Delta Y</th>
<th>Delta Z</th>
<th>3D RMSE</th>
<th>X RMSE</th>
<th>Y RMSE</th>
<th>Z RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>725567.1443</td>
<td>417622.3985</td>
<td>4976.106574</td>
<td>725567.129</td>
<td>417622.487</td>
<td>4976.114</td>
<td>0.090072</td>
<td>0.015262</td>
<td>-0.088459</td>
<td>0.00784</td>
<td>0.11202</td>
<td>0.04988</td>
<td>0.09569</td>
<td>0.03009</td>
</tr>
</tbody>
</table>
Figure 35: Sample site 2 project overview

Table 17: Sample Site 2a photogrammetry project quality

<table>
<thead>
<tr>
<th>Id</th>
<th>Model Point X</th>
<th>Model Point Y</th>
<th>Model Point Z</th>
<th>Check Point X</th>
<th>Check Point Y</th>
<th>Check Point Z</th>
<th>Delta Distance</th>
<th>Delta X</th>
<th>Delta Y</th>
<th>Delta Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>724730.1394</td>
<td>418074.4443</td>
<td>4997.128837</td>
<td>724730.165</td>
<td>418074.464</td>
<td>4997.146</td>
<td>0.036614</td>
<td>-0.02561</td>
<td>-0.01975</td>
<td>-0.01716</td>
</tr>
<tr>
<td>2</td>
<td>724817.4753</td>
<td>418043.7016</td>
<td>4976.716514</td>
<td>724817.514</td>
<td>418043.69</td>
<td>4976.717</td>
<td>0.04099</td>
<td>-0.0387</td>
<td>0.011551</td>
<td>0.00049</td>
</tr>
<tr>
<td>3</td>
<td>724961.8553</td>
<td>417946.9182</td>
<td>4953.350583</td>
<td>724961.886</td>
<td>417946.901</td>
<td>4953.345</td>
<td>0.038095</td>
<td>-0.00069</td>
<td>0.017199</td>
<td>0.005583</td>
</tr>
<tr>
<td>4</td>
<td>724923.0482</td>
<td>418066.4866</td>
<td>4975.54866</td>
<td>724923.032</td>
<td>418066.502</td>
<td>4975.525</td>
<td>0.032547</td>
<td>-0.0387</td>
<td>0.011551</td>
<td>0.00049</td>
</tr>
<tr>
<td>5</td>
<td>725003.1908</td>
<td>418043.7999</td>
<td>4950.578842</td>
<td>725003.17</td>
<td>418043.444</td>
<td>4950.573</td>
<td>0.029917</td>
<td>-0.01434</td>
<td>0.024722</td>
<td>0.008842</td>
</tr>
<tr>
<td>6</td>
<td>724969.9047</td>
<td>417935.6624</td>
<td>4957.024283</td>
<td>724969.858</td>
<td>417935.585</td>
<td>4956.988</td>
<td>0.087787</td>
<td>0.046725</td>
<td>0.07739</td>
<td>0.037283</td>
</tr>
<tr>
<td>7</td>
<td>725127.2766</td>
<td>417975.8014</td>
<td>4988.43222</td>
<td>725127.281</td>
<td>417975.835</td>
<td>4988.449</td>
<td>0.037835</td>
<td>0.00436</td>
<td>-0.03363</td>
<td>0.01678</td>
</tr>
</tbody>
</table>

3D RMSE | X RMSE | Y RMSE | Z RMSE
---|---|---|---
0.05269 | 0.02563 | 0.08976 | 0.02322
Table 18: Sample Site 2b photogrammetry project quality

<table>
<thead>
<tr>
<th>Id</th>
<th>Model Point X</th>
<th>Model Point Y</th>
<th>Model Point Z</th>
<th>Check Point X</th>
<th>Check Point Y</th>
<th>Check Point Z</th>
<th>Delta Distance</th>
<th>Delta X</th>
<th>Delta Y</th>
<th>Delta Z</th>
<th>3D RMSE</th>
<th>X RMSE</th>
<th>Y RMSE</th>
<th>Z RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>724942.1845</td>
<td>417983.4373</td>
<td>4950.543812</td>
<td>724942.274</td>
<td>417983.443</td>
<td>4950.57</td>
<td>0.093455</td>
<td>-0.08953</td>
<td>-0.00567</td>
<td>-0.026188</td>
<td>0.09037</td>
<td>-0.03385</td>
<td>0.02811</td>
<td>0.01950</td>
</tr>
<tr>
<td>6</td>
<td>724989.9552</td>
<td>417935.5503</td>
<td>4956.996672</td>
<td>724989.858</td>
<td>417935.585</td>
<td>4956.987</td>
<td>0.103575</td>
<td>0.097207</td>
<td>-0.00369</td>
<td>0.008672</td>
<td>0.09037</td>
<td>-0.03385</td>
<td>0.02811</td>
<td>0.01950</td>
</tr>
<tr>
<td>7</td>
<td>725003.2386</td>
<td>418048.4858</td>
<td>4989.511166</td>
<td>725003.17</td>
<td>418048.442</td>
<td>4989.485</td>
<td>0.085467</td>
<td>0.068599</td>
<td>0.043751</td>
<td>0.026166</td>
<td>0.09037</td>
<td>-0.03385</td>
<td>0.02811</td>
<td>0.01950</td>
</tr>
<tr>
<td>8</td>
<td>725127.2047</td>
<td>417975.8316</td>
<td>4988.44035</td>
<td>725127.281</td>
<td>417975.835</td>
<td>4988.449</td>
<td>0.076838</td>
<td>-0.07628</td>
<td>-0.00339</td>
<td>-0.00865</td>
<td>0.09037</td>
<td>-0.03385</td>
<td>0.02811</td>
<td>0.01950</td>
</tr>
</tbody>
</table>
Figure 36: Sample site 3 project overview

Table 19: Sample Site 3a photogrammetry project quality

<table>
<thead>
<tr>
<th>Id</th>
<th>Model Point X</th>
<th>Model Point Y</th>
<th>Model Point Z</th>
<th>Check Point X</th>
<th>Check Point Y</th>
<th>Check Point Z</th>
<th>Delta Distance</th>
<th>Delta X</th>
<th>Delta Y</th>
<th>Delta Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>726445.5694</td>
<td>418415.3649</td>
<td>4984.110201</td>
<td>726445.528</td>
<td>418415.308</td>
<td>4984.096</td>
<td>0.07177892</td>
<td>0.01415</td>
<td>0.05688</td>
<td>0.014201</td>
</tr>
<tr>
<td>3</td>
<td>726426.2623</td>
<td>418350.0878</td>
<td>4967.210079</td>
<td>726426.234</td>
<td>418350.134</td>
<td>4967.228</td>
<td>0.0570347</td>
<td>0.028254</td>
<td>0.04619</td>
<td>-0.01792</td>
</tr>
<tr>
<td>4</td>
<td>726460.6809</td>
<td>418338.3967</td>
<td>4965.057896</td>
<td>726460.703</td>
<td>418338.431</td>
<td>4965.022</td>
<td>0.04101875</td>
<td>0.019828</td>
<td>0.03434</td>
<td>0.003786</td>
</tr>
<tr>
<td>5</td>
<td>726495.2757</td>
<td>418338.0879</td>
<td>4962.498255</td>
<td>726495.31</td>
<td>418338.084</td>
<td>4962.509</td>
<td>0.03613002</td>
<td>0.03428</td>
<td>0.003916</td>
<td>-0.0107</td>
</tr>
<tr>
<td>6</td>
<td>726530.7314</td>
<td>418343.893</td>
<td>4965.329467</td>
<td>726530.742</td>
<td>418343.907</td>
<td>4965.323</td>
<td>0.02515781</td>
<td>0.02064</td>
<td>0.01459</td>
<td>0.006646</td>
</tr>
<tr>
<td>7</td>
<td>726561.8304</td>
<td>418322.8808</td>
<td>4961.691833</td>
<td>726561.823</td>
<td>418322.847</td>
<td>4961.687</td>
<td>0.03481816</td>
<td>0.07392</td>
<td>0.03766</td>
<td>0.004183</td>
</tr>
</tbody>
</table>

3D RMSE X RMSE Y RMSE Z RMSE
0.04703 0.02786 0.03629 0.01088

Table 20: Sample Site 3b photogrammetry project quality

<table>
<thead>
<tr>
<th>Id</th>
<th>Model Point X</th>
<th>Model Point Y</th>
<th>Model Point Z</th>
<th>Check Point X</th>
<th>Check Point Y</th>
<th>Check Point Z</th>
<th>Delta Distance</th>
<th>Delta X</th>
<th>Delta Y</th>
<th>Delta Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>726312.1394</td>
<td>418381.1988</td>
<td>4973.105311</td>
<td>726312.142</td>
<td>418381.311</td>
<td>4973.135</td>
<td>0.11511099</td>
<td>0.00264</td>
<td>-0.0264</td>
<td>0.10689</td>
</tr>
<tr>
<td>5</td>
<td>726275.3858</td>
<td>418429.7191</td>
<td>4985.356659</td>
<td>726275.363</td>
<td>418429.83</td>
<td>4985.364</td>
<td>0.11343122</td>
<td>0.022834</td>
<td>0.00734</td>
<td>0.00998</td>
</tr>
<tr>
<td>4</td>
<td>726296.8548</td>
<td>418453.0302</td>
<td>4983.420364</td>
<td>726296.886</td>
<td>418452.941</td>
<td>4983.463</td>
<td>0.09502427</td>
<td>-0.01312</td>
<td>0.0892505</td>
<td>-0.009996</td>
</tr>
<tr>
<td>3</td>
<td>726319.1615</td>
<td>418449.7335</td>
<td>4983.399744</td>
<td>726319.089</td>
<td>418449.77</td>
<td>4983.198</td>
<td>0.0743855</td>
<td>0.072468</td>
<td>0.0154764</td>
<td>0.003744</td>
</tr>
<tr>
<td>7</td>
<td>726317.044</td>
<td>418363.3391</td>
<td>4968.441039</td>
<td>726317.15</td>
<td>418363.29</td>
<td>4968.403</td>
<td>0.12287516</td>
<td>0.10603</td>
<td>0.0489086</td>
<td>0.038039</td>
</tr>
<tr>
<td>2</td>
<td>726342.7716</td>
<td>418385.1542</td>
<td>4965.413211</td>
<td>726342.727</td>
<td>418385.054</td>
<td>4965.406</td>
<td>0.1090561</td>
<td>0.044554</td>
<td>0.1002106</td>
<td>0.007211</td>
</tr>
</tbody>
</table>

3D RMSE X RMSE Y RMSE Z RMSE
0.10634 0.03771 0.08692 0.02756
Figure 37: Sample site 4 project overview

Table 21: Sample Site 4 photogrammetry project quality

<table>
<thead>
<tr>
<th>Id</th>
<th>Model Point X</th>
<th>Model Point Y</th>
<th>Model Point Z</th>
<th>Check Point X</th>
<th>Check Point Y</th>
<th>Check Point Z</th>
<th>Delta Distance</th>
<th>Delta X</th>
<th>Delta Y</th>
<th>Delta Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>725947.9917</td>
<td>418648.9537</td>
<td>5023.85468</td>
<td>725947.888</td>
<td>418649.044</td>
<td>5023.901</td>
<td>0.146906</td>
<td>-0.045533</td>
<td>-0.091324</td>
<td>0.10678</td>
</tr>
<tr>
<td>2</td>
<td>725934.7249</td>
<td>418631.4061</td>
<td>5031.671038</td>
<td>725944.923</td>
<td>418631.305</td>
<td>5031.624</td>
<td>0.239936</td>
<td>-0.082062</td>
<td>-0.101224</td>
<td>0.047038</td>
</tr>
<tr>
<td>3</td>
<td>725934.7105</td>
<td>418635.9373</td>
<td>5046.207549</td>
<td>725877.294</td>
<td>418635.915</td>
<td>5046.245</td>
<td>0.20204</td>
<td>0.184838</td>
<td>0.072366</td>
<td>-0.037851</td>
</tr>
</tbody>
</table>

3D RMSE | X RMSE | Y RMSE | Z RMSE
0.18311 | 0.15537 | 0.08734 | 0.04195
Figure 38: Sample site 5 project overview

Table 22: Sample Site 5 photogrammetry project quality

<table>
<thead>
<tr>
<th>Id</th>
<th>Model Point X</th>
<th>Model Point Y</th>
<th>Model Point Z</th>
<th>Check Point X</th>
<th>Check Point Y</th>
<th>Check Point Z</th>
<th>Delta Distance</th>
<th>Delta X</th>
<th>Delta Y</th>
<th>Delta Z</th>
<th>3D RMSE</th>
<th>X RMSE</th>
<th>Y RMSE</th>
<th>Z RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>727040.6634</td>
<td>416838.5182</td>
<td>5038.422453</td>
<td>727040.722</td>
<td>416838.5</td>
<td>5038.422</td>
<td>0.061389</td>
<td>-0.058624</td>
<td>0.018212</td>
<td>0.000453</td>
<td>0.09659</td>
<td>0.07711</td>
<td>0.07711</td>
<td>0.00857</td>
</tr>
<tr>
<td>2</td>
<td>726925.3345</td>
<td>417008.7217</td>
<td>5021.212534</td>
<td>726925.327</td>
<td>417008.804</td>
<td>5021.213</td>
<td>0.082673</td>
<td>0.007495</td>
<td>-0.082311</td>
<td>-0.009466</td>
<td>0.097458</td>
<td>0.094163</td>
<td>0.052264</td>
<td>-0.010828</td>
</tr>
<tr>
<td>3</td>
<td>727003.6299</td>
<td>416996.491</td>
<td>5035.396053</td>
<td>727003.552</td>
<td>416996.445</td>
<td>5035.394</td>
<td>0.095011</td>
<td>0.077909</td>
<td>0.046024</td>
<td>0.002033</td>
<td>0.097458</td>
<td>0.094163</td>
<td>0.052264</td>
<td>-0.010828</td>
</tr>
<tr>
<td>4</td>
<td>727043.7682</td>
<td>416800.8007</td>
<td>5038.270172</td>
<td>727043.674</td>
<td>416800.778</td>
<td>5038.271</td>
<td>0.094531</td>
<td>0.089531</td>
<td>0.08558</td>
<td>0.050774</td>
<td>0.100381</td>
<td>0.000914</td>
<td>-0.098779</td>
<td>0.017267</td>
</tr>
<tr>
<td>5</td>
<td>726959.2916</td>
<td>417024.6358</td>
<td>5026.31389</td>
<td>726959.206</td>
<td>417024.585</td>
<td>5026.314</td>
<td>0.099531</td>
<td>0.09558</td>
<td>0.050774</td>
<td>0.000914</td>
<td>0.100381</td>
<td>0.000914</td>
<td>-0.098779</td>
<td>0.017267</td>
</tr>
<tr>
<td>6</td>
<td>726964.8879</td>
<td>416996.9492</td>
<td>5028.590267</td>
<td>726964.887</td>
<td>416997.048</td>
<td>5028.573</td>
<td>0.100381</td>
<td>0.09558</td>
<td>0.050774</td>
<td>0.000914</td>
<td>0.100381</td>
<td>0.000914</td>
<td>-0.098779</td>
<td>0.017267</td>
</tr>
<tr>
<td>7</td>
<td>726931.1835</td>
<td>417047.9773</td>
<td>5023.285362</td>
<td>726931.275</td>
<td>417047.909</td>
<td>5023.297</td>
<td>0.111876</td>
<td>0.093476</td>
<td>0.063348</td>
<td>0.011638</td>
<td>0.117778</td>
<td>0.115961</td>
<td>-0.019249</td>
<td>0.005269</td>
</tr>
<tr>
<td>8</td>
<td>727028.799</td>
<td>416859.4581</td>
<td>5036.287269</td>
<td>727028.915</td>
<td>416859.478</td>
<td>5036.282</td>
<td>0.117778</td>
<td>0.115961</td>
<td>-0.019249</td>
<td>0.005269</td>
<td>0.09659</td>
<td>0.07711</td>
<td>0.07711</td>
<td>0.00857</td>
</tr>
</tbody>
</table>
References


Zingg, A.W., 1940. Degree and length of land slope as it affects soil loss in runoff. *Agricultural Engineering*, (21) 2: 59-64.